Analysis of Methodology for Motor Oil Time-Series Project

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1 Business Understanding

1.1 Objectives

The primary objective of this project is to experiment and develop practical experience in applying data science techniques to a business problem, followed by the goal of forecasting motor oil sales on a per-store basis. A secondary objective is to predict the future sales of specific products, which will further support inventory planning, supply chain optimization, and resource allocation.

To achieve these goals, the project will explore several related questions. For instance, how can the dip in sales in 2020 be accounted for in the modelling process? Furthermore, how should unique characteristics of the dataset, such as negative sales due to returns or high-value outliers, be addressed to improve the reliability of the models? Addressing these questions ensures that the project remains focused on delivering value while overcoming the challenges presented by the data.

From a business perspective, the project will be judged on its capacity to deliver clear insights into sales trends and anomalies. This translates to developing predictive models that effectively handle missing values, anomalies, and other unique data characteristics from a data mining perspective. Success criteria for data mining will include achieving forecasting models with acceptable performance metrics to ensure predictive accuracy. Additionally, the project will compare the performance of ARIMA and Prophet models, comparing their ability to forecast the sales data from our dataset.

1.2 Analysis of Resources

The project is supported by several resources that enable its successful execution. The team consists of three data science majors—Tina, Matthew, and James—who bring complementary skills in data analysis, Python, and neural networks.

Computing resources include access to college-provided facilities. Constraints while working on the project may include limited time for experimentation with models. The project offers the team academic and professional growth through the practical application of data science techniques.

1.3 Project Plan

This project was carried out over the course of the Fall 2024 semester at Winthrop University. The following plan was agreed upon at the beginning of the semester. Note that the weeks are relative to the semester, week 1 was focused on academic matters. Additionally, several weeks were missed due to severe weather and power outages.

1. **Weeks 2-3** - Data understanding phase
2. **Weeks 4-5** - Data exploration, cleaning
3. **Weeks 8-12** - Modelling phase
4. **Weeks 13-14** - Evaluation

2 Data Understanding

2.1 Initial Data

The dataset for this project was provided to the authors of this report by a local data science company in Rock Hill, SC, called Delta Bravo. The dataset was an anonymized, unclean data set that had been brought upon by real-world clientele. The data set contains a time series representing semi-aggregate motor oil sales data.

2.2 Description

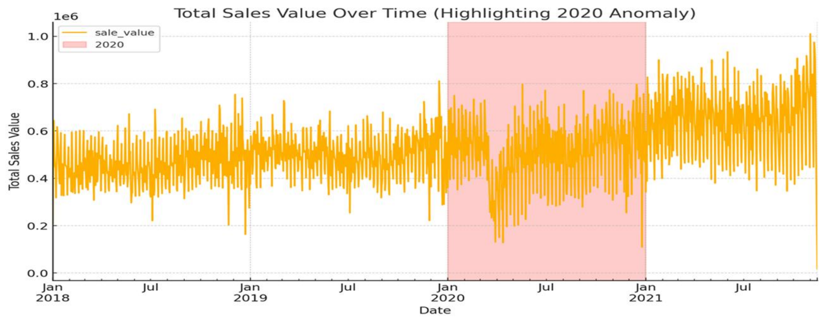
The data contained the following attributes:

1. **Invoice Date** - the date for which the total sales were recorded
2. **Customer Code** - a code that uniquely identifies the customer. These codes were anonymized prior to receiving them in order to protect confidentiality of the original client.
3. **Channel Text** - a label that represented the sales channel. This was almost entirely anonymized, and did not reveal any insights.
4. **Blend** - The type of oil being sold. A categorical attribute that describing whether the oil is conventional or synthetic. This attribute was labelled internally as ”conventional/synthetic”

5. **Variety and Size** - details the oil type and packaging
6. **Sale Value** - the target attribute, the total sales recorded for that row

2.3 Exploration

A notable feature of the dataset is the impact of the COVID-19 virus in the sales. A sharp decline can briefly be seen before slowly trending back up to pre-pandemic levels. Another key observation is the imbalance of both the spread of the location and the blend types.



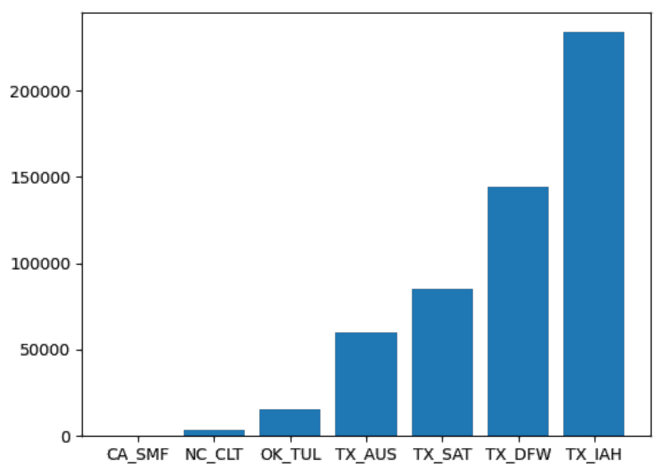
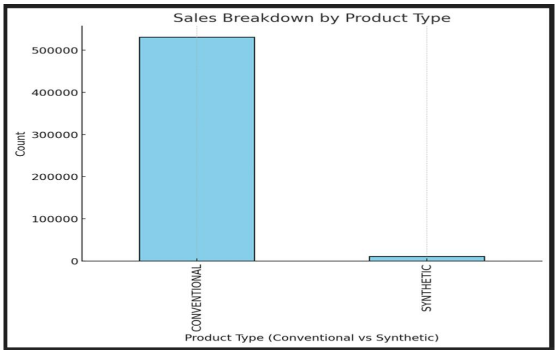


Figure 1: number of data instances by location



3 Data Preparation

3.1 Data Selection

Using criteria derived from information inferred during the data understanding phase, various attributes were dropped for the sake of this project, leaving only the invoice date as an index of the data set, sale values, and the location of the store from which the sale was made. Customer status was immediately removed due to its singular cardinality, ruling it out as a potential source of signal for the model. The attributes customer code and channel text were likewise removed due to their lack of relevance in forecasting sale values. Size and variety were not immediately discarded, but were later dropped as they suffered from imbalanced spread and did not lend to the task at hand.

3.2 Data Cleaning & Aggregation

Of the remaining attributes, two required additional cleaning: the invoice dates and the sale values. With respect to the invoice dates, there were some missing dates as well as duplicate values. It became clear that the dataset contained multiple sale values for the same days, and these values were aggregated on per-location basis. The missing dates had had their values using linear interpolation.

3.3 Data Integration

The resulting clean data was completely separated by location in order to preserve trend information related to local supply and demand as well as other regional factors.

4 Modelling

4.1 Modelling Technique

For this project, we utilized two time-series forecasting techniques, Prophet and ARIMA, to address our data mining problem. These two models were chosen, due to the educational nature of the project, to display the usage of explainable and unexplainable machine learning methods.

Prophet was chosen as the unexplainable "black box" method as it uses neural networks to forecast based on the time-series it was trained on. It is considerably more flexible and performs well when given noisy data. ARIMA, on the other hand, is a widely known statistical approach to time-series data. Its reliance on autoregressive (AR), differencing (I), and moving average (MA) terms allows for precise modelling of linear patterns in time-series data.

4.2 Test Design

To evaluate the two models' efficacy in forecasting the sales data, we performed a train-test split so that we can use the testing data to evaluate the models against actual data. By later testing these models, we can generate common time-series performance metrics like Root Mean Square Error (RMSE) and Akaike Information Criterion (AIC).

4.3 Building Models

By using AutoARIMA from the Python module "pmdarima" to automate parameter selection based on AIC optimization, we ensured optimal configurations of the model for daily and weekly data. The confidence intervals present in the ARIMA model provide great insights into ARIMA's strengths and limitations.

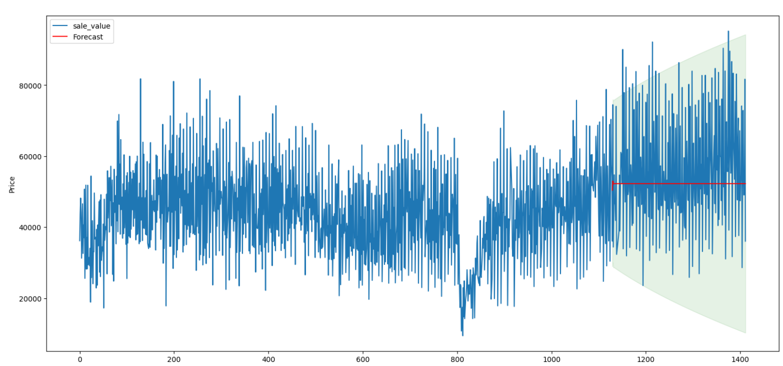


Figure 2: ARIMA forecast on TX AUS daily data

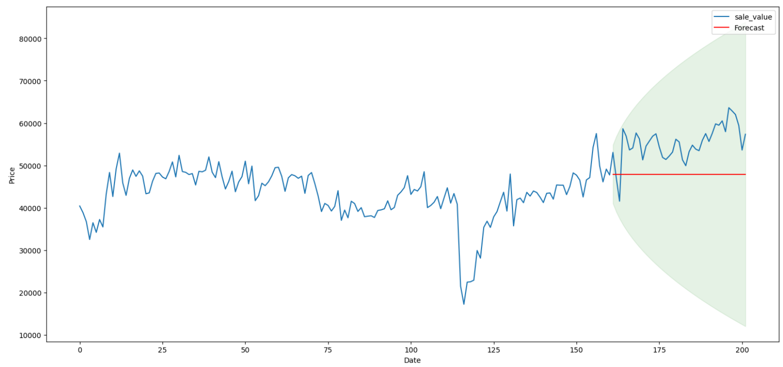


Figure 3: ARIMA forecast on TX AUS weekly data

For Prophet, we also trained models on both daily and weekly data. After training models without accounting for the COVID-19 lockdowns, we tried to incorporate them as custom one-off holiday periods. Those models took into account the dip in sales in 2020.

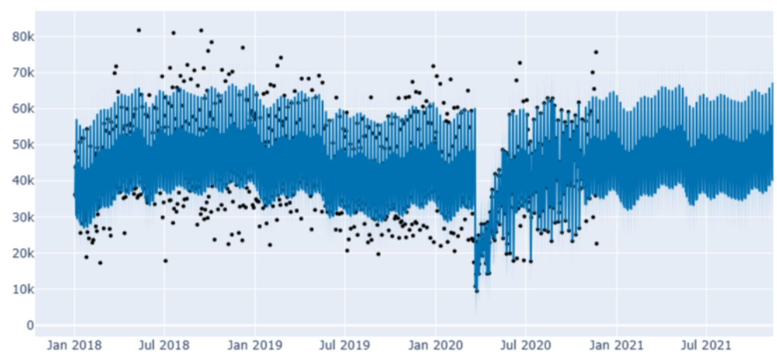


Figure 4: Prophet forecast on TX AUS daily data

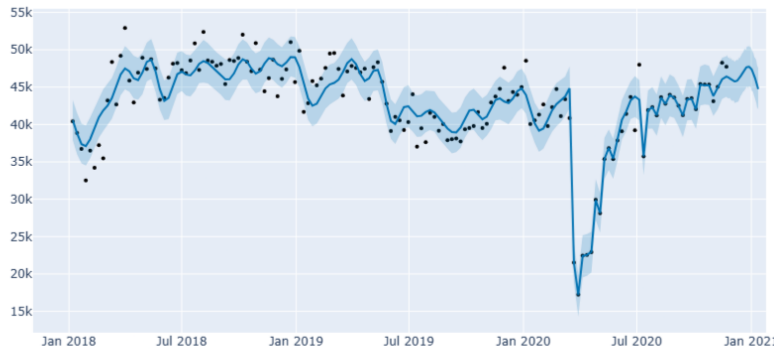


Figure 5: Prophet forecast on TX AUS weekly data

4.4 Individual Assessment

Prophet models that incorporated lockdowns outperformed their counterparts without external factors, demonstrating the importance of context-aware modelling. Weekly aggregation helped reduce noise, thus had the lowest AIC and RMSE scores.

ARIMA's linear approach limited its ability to capture non-linear patterns, and generally had higher AIC and RMSE scores. Again, Weekly aggregation produced better results by reducing noise from the daily data.

5 Evaluation

5.1 Assessment of Results

As stated previously, the metrics RMSE (Root Mean Squared Error) and AIC (Akaike Information Criterion) were used to evaluate the models. RMSE measures predictive accuracy by capturing the average magnitude of error, while AIC evaluates the model's goodness of fit while penalizing complexity.

ARIMA models performed well in regions with consistent and stationary sales patterns. For example, in TX DFW, ARIMA achieved an RMSE of 13,727 and an AIC of 34,327. However, in more volatile regions like TX IAH, ARIMA's RMSE increased to 18,734, and its AIC rose to 45,219.

Prophet consistently outperformed ARIMA across all regions, demonstrating superior accuracy and adaptability. For instance, in TX DFW, Prophet achieved an RMSE of 11,429 (a 16.7 percent improvement over ARIMA) and an AIC of 33,218. Additionally, In regions like CA SMF and TX SAT, where ARIMA performed relatively well, Prophet still demonstrated improved results.

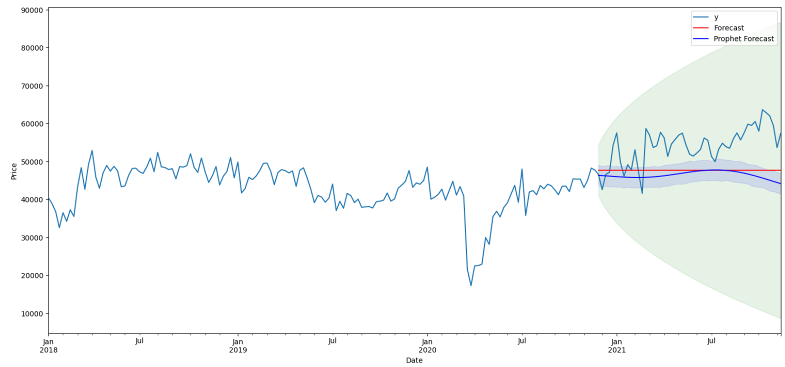


Figure 6: Comparing Prophet (Blue) and ARIMA (Red) with TX AUS forecast

5.2 Finalized Models

The final models can be broken down into several different categories. Firstly, the type of model, ARIMA or prophet. Secondly, the models were trained on different versions of the data. The data was aggregated either on a daily or weekly basis. Additionally the initial test train split was inadequate because the data had a sudden change in trend very close to the split date. To ensure model efficacy the models were also trained on just the original test data to see if it could accurately capture the new trend. Models were trained on all combinations of the aforementioned factors for at least one of the locations.

5.3 Future Action

Some features of the dataset, namely the variety of the oil, were not treated to the fullest extent that they could have been in this project. This is a weak point of the approach that was taken, and future efforts attempting to mitigate the imbalanced spread of the blend may take into account the effect of this and the varieties of oil to yield further insights about inventory and sales at a more granular level.

5.4 Conclusion

The ultimate purpose of this project was to acquaint the authors with time-series and different methodologies involved in the treatment of such. Thus it was decided that the project would act as a survey of both ARIMA and Neural Network based models, and as a comparison of the two. From the results of the modelling stage, we can conclude that both types of models tend to capture similar trends, but with varying levels of granularity and confidence. ARIMA casts a far wider net, so to speak, and as such values are far more likely to fall in its confidence interval. The prophet model, on the other hand, tends to be more confident in its prediction, however, if something unexpected happens, the actual data can fall far outside of its predicted bounds. Prophet is able to produce a forecast line that is more nuanced, though, and may be able to capture smaller, temporary noise slightly better as a result.